



**Research article**

## **The prediction Brahman X Charolais and Brahman X Thai native with Evolutionary-Extreme Learning Machine in Phetchabun Province Thailand.**

**Worachai Srimuang<sup>1</sup> Janjira Tohwankaew<sup>2</sup> and Piphat Chanartaeparporn<sup>2\*</sup>**

<sup>1</sup>*Department of Technology Computer, Faculty of Agricultural Technology and Industrial Technology, Phetchabun Rajabhat University, Phetchabun, 67000, Thailand*

<sup>2</sup>*Department of Animal Science, Faculty of Agricultural Technology and Industrial Technology, Phetchabun Rajabhat University, Phetchabun, 67000, Thailand*

**ARTICLE INFO**

**Article history**

Received: 25 March 2023

Revised: 21 June 2023

Accepted: 28 June 2023

Online published: 29 June 2023

**Keyword**

*Thai beef cattle*

*Growth rate and body weight*

*Evolutionary-ELM*

*Differential evolution*

*Linear regression*

**ABSTRACT**

**The purpose of this study was to develop a growth forecasting model for Stocker Cattle Producers. In the long yearling (12-24 months) breed, only Brahman X Charolais and Brahman X Thai native were selected, all of which are 50 % breed (F1) from 17 Sub-Districts in Muang District, Phetchabun, Thailand. There were three different forecasting model methods: 1) Extreme Learning Machine (ELM); 2) Weighted- Extreme Learning Machine (Weighted ELM) and 3) Evolutionary- Extreme Learning Machine (ELM). The surveyed data were taken through the Feature Selection process to select factors affecting the relationship between feed intake, along with the growth rate according to body weight during the month. The recording data was then used to create a forecasting model to create an estimate of the weight of beef cattle that is close to the best growth. The results indicated that Evolutionary-ELM was able to gain weight during the 19th months on an average of up to 500 kilograms after the cattle were fed continuously until the 24th months. The prognostic results of Brahman X Charolais beef cattle could be predicted as an average weight of 604.088 kilograms an error at  $R^2=0.9327$ , with growth rate  $Y=30.562x-129.40$ ,  $RMSE=0.130$ ,  $MSE=0.107$ . Brahman X Thai native beef cattle could be predicted for 509.982 kilograms an error at  $R^2=0.9706$ , with growth rate  $Y=28.098x-164.37$ ,  $RMSE=0.117$ ,  $MSE=0.083$ . The Evolutionary-ELM algorithm learns and adjusts the weights to optimize the best results for each month's growth period, which reduces the problem of margin, keeping the distance not too high or too low. It can be used as a model for raising large beef cattle weighing 550-650 kilograms, allowing farmers who are interested in beef cattle farming to compare the model with their decision-making.**

### **Introduction**

Thailand's current livestock production system faces a competition for natural resources (Steinfeld et al., 2006), growth competition to keep up with the demand for beef consumption along

with the development of the production potential of each farm, (Krasachat, 2008) and farm location in a variety of agricultural areas, that can select various raw materials for food to reduce costs considerably. In addition, farmers must also know which system

\*Corresponding author

E-mail address: piphat.cha@pcru.ac.th (P. Chanartaeparporn)

Online print: 29 June 2023 Copyright © 2023. This is an open access article, production, and hosting by Faculty of Agricultural Technology, Rajabhat Maha Sarakham University. <https://doi.org/10.14456/paj.2023.20>

to raise, therefore, they could select the appropriate cattle breeds and methods for raising beef cattle in the tropics. Such environment is a key factor that affects the tradition of livestock, agriculture, and agricultural products. It determines what kind of farm should be. Beef cattle farms in each Sub-district of Mueang Phetchabun District are different according to the area conditions. It largely depends on the capital that the farmers can invest in food, whether roughage, concentrate, natural plant foods (Ogino et al., 2016). Furthermore, beef cattle feeding needs to be calculated according to age - the most suitable age range, including controlling the temperature, humidity, internal cooling airflow of the farm or house. These factors directly and indirectly affect beef cattle (Khunchaikarn et al., 2022).

100 percent European breed with large size tends to be raised in hot and humid climates. Originally, they were accustomed to cold weather which directly affects the slow growth. Therefore, there the breed must be crossed with Thai beef cattle that are resistant to hot weather and insects in order to bring their strengths of each breed to improve into breeds of beef cattle that can withstand the environment of Thailand (Na-Chiangmai, 2002). The Angus Beefmaster Wagyu breed is commonly used as a breeder and bred with Thai native, which becomes a mixed breed between Brahman X Angus, Brahman X Charolais, Brahman X Thai native, and Charolais X Thai native (Bunmee et al., 2018). There are also Thai Brahman X Simmental-Brahman (Kabinburi Beef Cattle), mixed breeds raised in the eastern part of Thailand, and supported from the Department of Livestock Development and the Association of Beef Cattle Farmers in recommending weight gain during the yearling (12 to 18 or 20 months), and long yearling (12,18 to 24 months) (Boonprong et al., 2008), which the body weight should be 500 kilograms or more according to the criteria for not being forced the price down when selling and to meet the export demand for the modern market, including expanding the market to the premium market (Osothongs et al., 2016).

Extreme Learning Machine (ELM) is based on Least-Square Mathematics on architecture structure of Single Hidden Layer Feedforward Networks (SLFNs). It can be used to solve estimation problems, regression problems, or to

create classification models. Therefore, the aim of this study is to generate a high-scoring regression estimate model from a simple and fast workflow. The experiment consisted of 3 algorithms: ELM (Huang, et al., 2006), W-ELM (Zong et al., 2013), and E-ELM (Zhu et al., 2005) with data on stocker cattle producers of Brahman X Charolais and Brahman X Thai native during the long yearling period of 12-24 months including predicting the body weight of beef cattle to be 500-600 kilograms or more which is the appropriate body weight for sale. Also, it was to provide and together with the production of crossbred beef cattle between foreign breeds and native breeds that are becoming popular, is the use of machine learning, estimation, forecasting, and growth in starting to raise beef cattle aged 12-24 years to be ready for local and international market demands, including farmers who are interested in beef farming have used the comparisons from the model to make the decision (Osothongs et al., 2016).

## Materials and methods

### *Data collection of beef cattle in Phetchabun Province*

Beef cattle data collection was conducted using a survey on beef cattle production and utilization in beef cattle farm management. In 17 Sub-Districts with 221 villages in Muang District, Phetchabun Province (Figure 1) features of beef cattle breeding consist of 55 attributes, surveyed by Animal Science students (purposive sampling) (Boyce & Neale, 2006), Department of Animal Science, Faculty of Agricultural Technology and Industrial Technology, Phetchabun Rajabhat University, from March 2020 to April 2022.

Raw data obtained from a survey of the number of raising foreign breeds of beef cattle such as Angus Beef Master Brahman Charolais for being breeders revealed that some farms still have a small amount of Wagyu beef cattle, Thai native beef cattle, and hybrids raised for use in small farms. It indicates the size of the farm, production volume, and export demand. It can be noted that the most popular breeds of beef cattle are Brahman X Charolais and Brahman X Thai native crossbreds. The data are divided by district in Table 1.



**Figure 1** Map of Mueang Phetchabun District, Phetchabun Province

**Table 1** Population of beef cattle (12- 24 months old) in 17 Sub-Districts, Mueang Phetchabun District Phetchabun Province

District	Angus	Beef Masther	Brahman	Brahman X Angus	Brahman X Charolais	Brahman X Thai native	Charolais	Charolais X Angus	Hindu Brazilian	Thai native	Wagyu	All
Bankhok	0	0	3	0	85	46	0	0	10	22	0	166
Bantok	14	14	0	0	7	0	17	0	0	1	0	53
Chonprai	0	0	2	0	44	8	0	0	5	26	0	85
Dongmoonlek	4	0	0	5	71	0	0	0	5	12	0	97
Huaisakae	2	11	6	0	158	186	25	0	49	14	0	451
Huaiyai	0	0	0	0	80	0	23	0	1	0	0	104
Naimuang	0	0	1	0	35	0	0	0	3	0	0	39
Namron	0	0	0	0	111	0	2	0	0	38	0	151
Nangua	0	0	0	0	108	0	0	0	3	53	0	164
Napa	0	0	0	0	26	0	0	0	4	15	0	45
Nayom	0	1	0	0	70	0	32	0	0	21	28	152
Palao	0	0	0	0	296	20	44	0	4	26	0	390
Rawing	1	0	10	0	105	132	0	0	42	18	0	308
Sadiang	0	0	0	0	5	7	0	0	0	3	0	15
Tabo	1	0	0	0	211	126	2	14	13	30	0	397
Tapol	5	0	0	0	207	14	10	0	23	38	0	297
Wangchomphu	0	0	73	0	47	12	2	0	14	15	0	163
All Beef	27	26	95	5	1,666	551	157	14	176	332	28	3,077

**Extreme Learning Machine (ELM)**

Extreme Learning Machine is one of Machine Learning on least-square computational foundation architectures with single-hidden layer feedforward networks (SLFNs) (Huang et al., 2006), starting with

input to the Input layer, and learning sample that is made as a parameter represented by  $x_n$  according to each data. Input is calculated with learning rate obtained and adjusted to weights  $W_{i,j}$ . Bias value  $\beta_j$  is automatically defined and sent to hidden layer  $H =$

$[h(x_1); h(x_2); \dots, h(x_n)]$ , without parameterizing the hidden layer output (with  $L$  nodes) can be parameterized with the activation function  $g(x)$ . It results in the optimal weight  $\beta_{j,k}$  without iteration once it reaches the output layer. The result is in the form of vector according to the number of target vector  $T$ , making the answer more accurate, and transfer function changes from linear and nonlinear, Equations (1).

$$H\beta = T \text{ or } \|H\beta - T\| = 0 \tag{1}$$

*Weighted Extreme Learning Machine (Weighted ELM)*

Weighted adjustment in weighted learning between the majority class and the minority class is designed to be used in handling imbalanced data distribution. It was improved from Extreme Learning Machine to be more efficient in classifying imbalanced data passing the training data to  $x_i$  value. If the calculation result of  $x_i$  has the minority class, weights for  $x_i$  would be added to give more weight. However, if the group belongs to the majority class,  $w_{ii}$  weighting would decrease. Resolving this problem would bring about a balance between the two data groups (Zong et al., 2013), including optimization of weights in multiplication between diagonal weight matrix.

$$\beta = H^+T = \begin{cases} H^T \left( \frac{1}{c} + WHH^T \right)^{-1} WT & \text{when } N < L \\ \left( \frac{1}{c} + H^TWH \right)^{-1} WH^T T & \text{when } N \geq L \end{cases} \tag{2}$$

*Evolutionary-Extreme Learning Machine (E-ELM)*

The operation of ELM algorithm randomly selects input weights and Bias is spent most of the time calculating and adjusting the parameters and recording the value when learning is completed in each cycle. Such operation may include output weights in response with Bias that may not be appropriate or necessary for learning, including adding more hidden nodes for tuning. This results in slower performance of the ELM algorithm (Huang et al., 2006). This flaw requires improvement in the addition of

hybrids, Differential Evolution Algorithm (DE) (Storn & Price, 1997), and Moore–Penrose Generalized Inverse (Thapa et al., 2018).

First: a population is defined. Each individual in the population consists of a set of input weights and hidden biases:  $\theta = [w_{11}, w_{12}, \dots, w_{nK}, \dots, b_1, b_2, \dots, b_K]$  all  $w_{ij}$  and  $b_j$  values are randomly initialized within the range of  $[-1, 1]$ .

Second: Each individual is set to weights and its Bias is calculated analytically using MP generalized inverse. As is done in ELM  $\hat{B} = H^+T$  (Ghosh & Verma, 2003) instead of iterative tuning and sending to the output weights. Then, fitness of each individual is evaluated which Cost Function (E) calculates Evaluation metrics root mean squared error (RMSE).

$$E = \sqrt{\frac{\sum_{j=1}^N \|\sum_{i=1}^K \beta_i g(w_i x_j + b_j) - t_j\|_2^2}{m \times N}} \tag{3}$$

Third: After calculating Fitness, 3 steps are used in DE: mutation, crossover (CR), and selection. During selection, individual parameter (NP) are compared with the original vectors. Once the vectors gain better fitness values, they are passed to the next generation (G) (Zhu et al., 2005) so that the neural network training include the fitness values (validation RMSE) into the selection process with the norm of output weights  $\|\beta\|$  (Bartlet, 1996). When the fitness values are slightly different for each individual, the weighted result is chosen as the new population  $\theta_{i,G+1}$ .

*Activation function in Extreme Learning Machine*

For activation function, the mathematical theory is applied to the hidden layer output vector  $L$  dimensionality is passed to the parameters  $(a_i, b_i)$  in the hidden layer node function  $h(x)_i = G(a_i, b_i, x)$  (Huang et al., 2006), Values are generated randomly based on a continuous probabilistic distribution of data in order to

follow a planned learning style. Optimization provides classification with the trade-off constant (C) (Zong et al., 2013) and F, CR and NP Function (Zhu et al., 2005). Calculating the hidden layer in  $\beta$  values before passing to the output layer increases

the distance between small data to be similar in width to large data for learning. The equation for activation function to linear function, nonlinear function, and continuous data (Huang & Babri, 1998) is as follows:

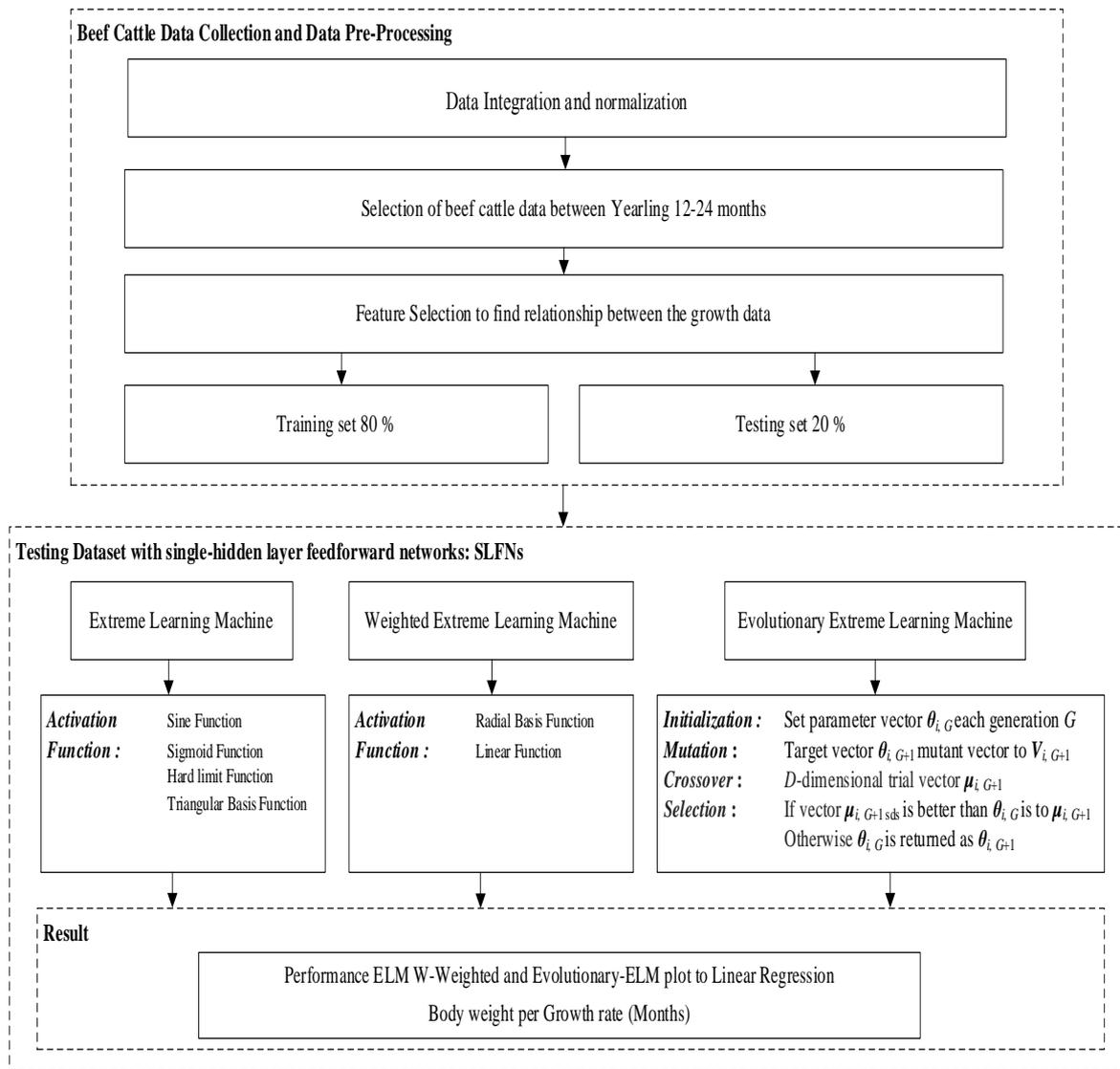
**Table 2** Activation function in ELM, Weighted-ELM, and Evolutionary-ELM

Algorithms	Activation Function	C	F	CR	NP	Equation	Ref
ELM	Sine	-	-	-	-	$G(a, b, x) = \sin(q + 2p)$	(4)
	Sigmoid	-	-	-	-	$G(a, b, x) = \frac{1}{1 + \exp(-(a \cdot x + b))}$	(5)
	Hard limit	-	-	-	-	$G(a, b, x) = \begin{cases} 1 & \text{if } a \cdot x - b \geq 0 \\ 0 & \text{otherwise} \end{cases}$	(6)
	Triangular Basis	-	-	-	-	$G(a, b, x) = \text{tribas}(N, FP)$	(7)
W-ELM	Radial Basis	$2^2 - 2^8$	-	-	-	$G(a, b, x) = \exp\left(\frac{\ x - x_i\ }{2\sigma^2}\right)$	(8)
	Linear	$2^2 - 2^8$	-	-	-	$G(a, b, x) = f(x) = a + bx$	(9)
E-ELM	-	-	0.3 - 0.8	0.5 - 1	50-130	$E = \sqrt{\frac{\sum_{j=1}^N \ \sum_{i=1}^K \beta_i g(W_i \cdot X_j + b_j) - t_j\ _2^2}{m \times N}}$	(10)

C= trade-off constant C, F= fitness function, CR=crossover rate, NP= Individual Parameter.

In this experiment in Figure 2 we focused on Stocker Cattle Producers for sale during the long yearling 12-24 months by selecting the population from the total number of beef cattle from 1-60 months. We selected 1,666 Brahman X Charolais beef cattle from the total data, leaving only 1,170 during the long yearling period, with data sharing of Train 930 (80%), Test 234 (20%), and 503 from 551 Brahman X Thai native

crossbred cattle, with data sharing of Train 401 (80%) and Test 102 (20%). Both are 50% breed (F1), with up to 90%, 75% breed (F2) for 7.2%, and 87.5% breed (F3) for 2.8% which is the most numerous in almost every Sub-district from 17 Sub-Districts (Table 1) due to the support between the Department of Livestock, Mueang Phetchabun District.



**Figure 2** Flow chart of the research methodology.

## Results and Discussion

### Feature selection beef cattle data for training data

A total of 55 features in the dataset has been brought through the feature selection. Some features are not relevant to the data and to select correlated features through multivariate filter methods (Labani et al., 2018), with greedy stepwise selection, selecting predictor variables in forward and backward searches. All three methods were predictive variables with correlation that is suitable for prediction and regression, started by taking the training dataset through the python sklearn function and matplotlib, the most important features would be selected in forward, kept in  $S$ . Then, it is examined in order to find the backward

relationship  $T$ , to find the highest score not more than 1 to be used as a feature option, calculate with the number of features and the entropy value used for analysis was  $(1 - 1/e) > 0.67$ .

The results of the three algorithms showed that the greedy stepwise selection method was able to select 17 correlated and appropriate features, 24 features for forward selection and 25 features for backward selection, respectively. Furthermore, the feature selection was used to analyze the efficiency as well to test for accuracy. The accuracy of the prediction model was 0.914, 0.830, and 0.811, respectively. Therefore, the greedy stepwise feature selection method was most suitable and the selected features are summarized in Table 3.

**Table 3** Multivariate filter selection feature importance methods

Data type	Feature name
Continuous (10 Features)	Farm_rising, Grass_area, Farm_system, feeding_time, Green_roughages, Dry_roughages, Ensilage_roughages Concentrate, Growthrate_Month, BodyWeight
Discrete (3 Features)	District, Experience, TMR
Nominal (4 Features)	Vaccination_Deworming, Disinfection_system, Mineral, Water

*Result of Extreme Learning Machine and Weighted-Extreme Learning Machine*

According to weight prediction of beef cattle using ELM, both breeds are grown-up, having an initial weight of 200 kilograms. Data are consolidated from 18 to 21 months. Learning with 4 activation functions.

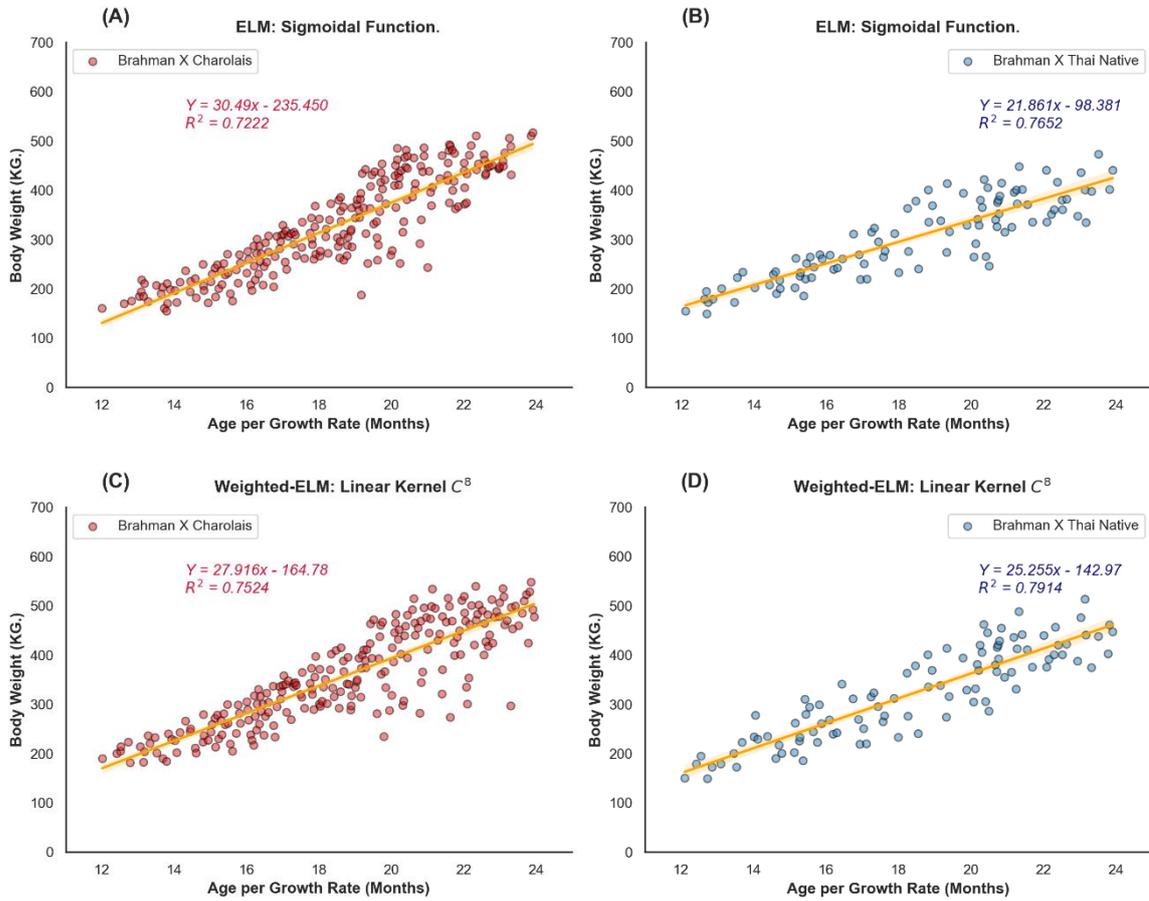
Prediction equation  $Y = bx + a$ , which the dependent variable is  $Y$ , the growth weight  $x$  is the independent variable that the period of raising long yearling is from 12-24 months,  $b$  is the slope, which is  $a$  value indicating a change in growth rate for 1 month/weight of beef cattle. It would change according to month/weight. This is called regression coefficient,  $a$  is a constant, also known as the  $y$  intercept, when  $x$  equals 0. All results shown in this paper has been displayed as scatter in linear regression. Figure 3 ELM Sigmoidal Function (A) Brahman X Charolais beef cattle had  $R^2 = 0.7222$ ,  $Y = 30.49x - 235.450$ . When fed until the 24<sup>th</sup> months, an estimated weight would be 496.31 kilograms, which a weight cannot be no more than 500 kilograms. ELM Sigmoidal Function (B) Brahman X Thai native beef cattle  $R^2 = 0.7652$ ,  $Y = 21.861x - 98.381$  are fed up to 24 months, a weight would be 426.283 kilograms but were scattered quite a lot. Therefore, ELM algorithm has been optimized. In case of unbalanced data with trade-off constant ( $C$ ) from  $2^2$  to  $2^8$ , calculated with RBF and linear Kernel, Weighted-ELM can produce more good weight and the distribution rate has decreased to some extent. The best result for

this algorithm is linear Kernel  $C = 2^8$  ( $C$ ) for Brahman X Charolais  $R^2 = 0.7524$ ,  $Y = 27.916x - 164.78$  a weight would be 505.204 kilograms, and linear Kernel  $C = 2^8$  ( $D$ ) Brahman X Thai native  $R^2 = 0.7914$ ,  $Y = 25.255x - 142.97$  a weight would be 463.16 kilograms.

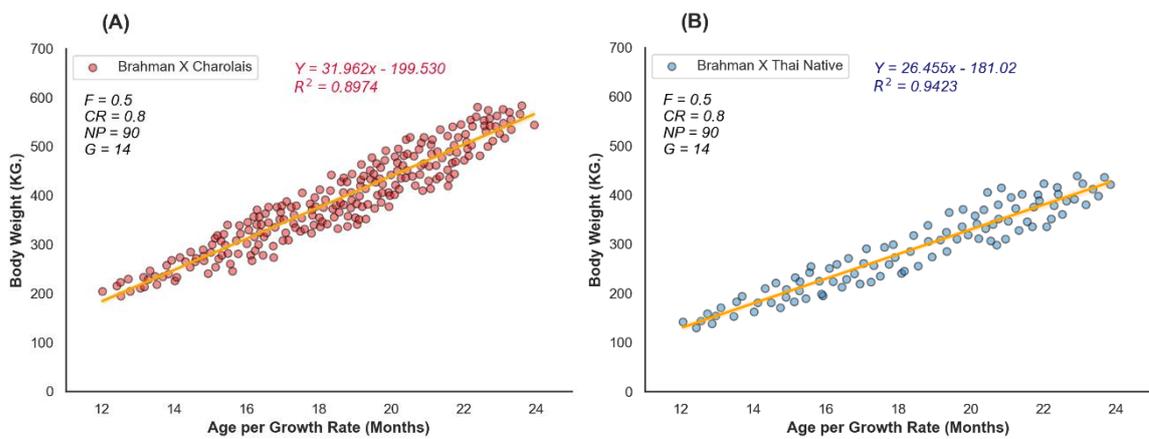
*Result of Evolutionary Extreme Learning Machine*

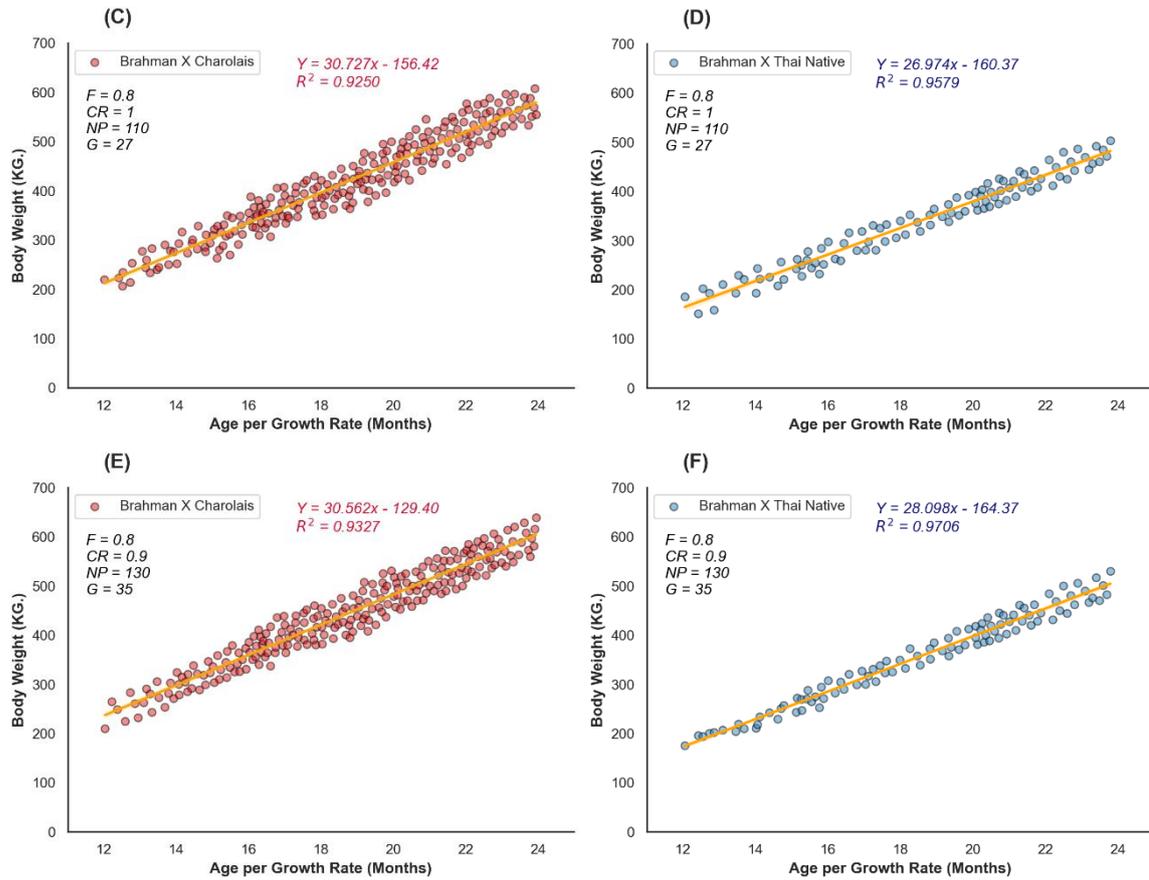
Optimizing beef weight with E-ELM is a more complex process than ELM. It is calculated according to Differential Evolution (DE). Individual parameter ( $NP$ ) vectors  $\{\theta_{i,G} | i = 1, 2, \dots, NP\}$  were adjusted according to the population in each generation ( $G$ ) to find appropriate input weights and optimal hidden biases (Zhu et al., 2005). Thereafter, output weights are calculated with MP generalized inverse, including iteration and mutation for each model until the answer was appropriate. Target vector is assigned based on the mutation  $V_{i,G+1}$ .

Parameters of differential evolution (DE) used in E-ELM are set according to the Brahman X Charolais 234 and Brahman X Thai native by 102 points. Parameter of fitness function ( $F$ ) is used to control differential variation; CR Parameter for adjusting crossover; and G Parameter for adjusting the number of generations, starting at 1 and 0.8, respectively. With every simulation, individual parameter ( $NP$ ) is gradually increased and the best effective result is selected as the final result. All results shown in this paper are plotted as linear regression.



**Figure 3** Results of the prediction on ELM Sigmoidal Brahman X Charolais (A) ELM Sigmoidal Brahman X Thai native (B) compared with W-ELM Linear Kernel  $C^8$  Brahman X Charolais (C) W-ELM Linear Kernel  $C^8$  Brahman X Thai native (D).





**Figure 4** Results of E-ELM CR=0.8, NP=90, G=14 Brahman X Charolais (A) Brahman X Thai native (B) compared CR=1, NP=110, G=27 Brahman X Charolais (C) Brahman X Thai native (D) and CR=0.9, NP=130, G=35 Brahman X Charolais (E) Brahman X Thai native (F).

*Comparison results between ELM, Weighted-ELM, and Evolutionary-ELM*

It can be noted that the growth forecasting models of Brahman X Charolais and Brahman X Thai native beef cattle are compared with 3 models, starting from 4 calculation packages of ELM activation function. Poor results showed in linear growth rates with the lowest R2 and Y values. Weighted-ELM 2 activation function algorithm with control parameter to optimizing trade-off constant (C) started from 22 until 28 Linear Kernel Brahman X Charolais R2 between 0.7801 – 0.8510, and Y was at the level of  $24.87x - 255.011$  until reaching  $29.514x - 106.05$  - a slight increase. But Brahman X Thai native, the mathematical model gained a better value due to the small size of the test data, Evolutionary-ELM and could adjust many kinds of parameters making the experimental results came out very well.

Yet, there is a limitation, if the parameters are adjusted too much, it would cause over fitting for both Weighted-ELM and Evolutionary-ELM algorithms. All experimental results are shown in Table 4. Basic metrics for measuring the performance of the 3 algorithm models, R2, RMSE, and MSE are shown in Table 5.

*Time Summary of results for ELM, Weighted-ELM, and Evolutionary-ELM*

The time benchmark in seconds demonstrated the ability in learning data from the training package. All algorithms did not have much difference in learning time, about 1-2 seconds. It would take more time for the test dataset to adjust weight in Weighted-ELM for both breeds, as well as the weight adjustment from evolution. From adjusting fitness crossover to get the best generation, it took quite a lot of time but gave the best results. Therefore, the time efficiency depends on the adjustment of control parameters.

**Table 4** The results of linear regression depend on the correlation of the predictors

Models	Activation Function	Control Parameters				Brahman X Charolais		Brahman X Thai native	
		C	F	CR	NP	R <sup>2</sup>	Y	R <sup>2</sup>	Y
ELM	Sigmoid	-	-	-	-	0.7222	30.49x – 235.450	0.7652	21.861x – 98.381
	Hard limit	-	-	-	-	0.5849	24.262x - 238.916	0.6718	13.241x - 139.221
	Sine	-	-	-	-	0.6810	21.982x - 220.733	0.7543	21.861x – 81.81
	Triangular Basis	-	-	-	-	0.7047	22.392x – 248.87	0.7276	23.03x - 79.692
	Linear Kernel	2 <sup>2</sup>	-	-	-	0.7801	24.87x – 255.011	0.7655	24.154x – 80.339
W-ELM	Linear Kernel	2 <sup>4</sup>	-	-	-	0.8171	24.723x - 219.77	0.8052	23.192x - 68.021
	Linear Kernel	2 <sup>8</sup>	-	-	-	0.8510	29.514x – 106.05	0.8256	25.958x – 114.05
	RBF Kernel	2 <sup>2</sup>	-	-	-	0.7519	30.65x – 210.318	0.7093	26.12x – 167.122
	RBF Kernel	2 <sup>4</sup>	-	-	-	0.7807	29.215x - 291.823	0.7276	34.824x - 251.371
	RBF Kernel	2 <sup>8</sup>	-	-	-	0.8291	23.213x - 268.732	0.7486	27.089x - 124.03
-	-	0.3	0.5	50	0.8301	28.21x – 251.674	0.8823	22.614x – 165.54	
-	-	0.4	0.8	70	0.8604	28.544x – 223.24	0.91	25.128x – 132.441	
E-ELM	-	-	0.5	0.8	90	0.8974	31.962x-199.530	0.9423	26.455x – 181.02
	-	-	0.8	1	110	0.9250	30.727x – 156.42	0.9579	26.974x – 160.37
	-	-	0.8	0.9	130	0.9327	30.562x – 129.40	0.9706	28.098x – 164.37

**Table 5** Parameters and statistical results obtained from the regression analysis

Models	Activation Function	Control Parameters				Brahman X Charolais			Brahman X Thai native		
		C	F	CR	NP	R <sup>2</sup>	RMSE	MSE	R <sup>2</sup>	RMSE	MSE
ELM	Sigmoid	-	-	-	-	0.7222	0.834	0.741	0.7652	0.619	0.560
W-ELM	Linear Kernel	2 <sup>8</sup>	-	-	-	0.8510	0.512	0.449	0.8256	0.373	0.122
E-ELM	-	-	0.8	0.9	130	0.9327	0.130	0.107	0.9706	0.117	0.083

**Table 6** Training and testing time of ELM, Weighted-ELM, and Evolutionary-ELM

Models	Activation Function	Control Parameters				Brahman X Charolais		Brahman X Thai native	
		C	F	CR	NP	Training Time	Testing Time	Training Time	Testing Time
ELM	Sigmoid	-	-	-	-	14.3589 s	15.0526 s	10.1198 s	12.0934 s
	Hard limit	-	-	-	-	13.2406 s	14.6078 s	9.3537 s	13.9845 s
	Sine	-	-	-	-	13.0731 s	13.0996 s	10.4324 s	13.0554 s
	Triangular Basis	-	-	-	-	13.4812 s	16.8796 s	7.9864 s	12.3788 s
	Linear Kernel	2 <sup>2</sup>	-	-	-	16.9811 s	230.2409 s	10.7426 s	135.8208 s
W-ELM	Linear Kernel	2 <sup>4</sup>	-	-	-	15.2644 s	291.0184 s	12.3478 s	142.8494 s
	Linear Kernel	2 <sup>8</sup>	-	-	-	14.0092 s	218.3181 s	11.9657 s	102.3601 s
	RBF Kernel	2 <sup>2</sup>	-	-	-	18.0901 s	232.0067 s	12.0984 s	233.0361 s
	RBF Kernel	2 <sup>4</sup>	-	-	-	12.3981 s	323.2617 s	12.5712 s	202.8940 s
	RBF Kernel	2 <sup>8</sup>	-	-	-	14.9609 s	350.6311 s	12.7573 s	224.8405 s
-	-	0.3	0.5	50	14.0424 s	719.2998 s	16.0970 s	535.3501 s	
-	-	0.4	0.8	70	13.9451 s	752.4310 s	13.0912 s	501.2128 s	
E-ELM	-	-	0.5	0.8	90	15.0381 s	810.9812 s	12.7811 s	556.7491 s
	-	-	0.8	1	110	14.8419 s	819.2317 s	13.1372 s	550.1275 s
	-	-	0.8	0.9	130	15.6323 s	822.0912 s	12.9539 s	601.9523 s

The purpose of this study was to develop an efficient growth-based beef weight equation for mixed beef cattle raised in tropical regions and growth forecasting model of stocker cattle producers in long yearling (12-24 months), using three modeling algorithms which are ELM, Weighted-ELM, and Evolutionary-ELM. The data collected in the survey area consisted of 55 features that affected farming. This was taken through the feature selection process to find relationship of true hidden subset from multivariate filter methods. Factors affecting the growth of 17 features were found and it was divided into learning data 80 % and testing data 20 %. After that, ELM, Weighted-ELM, and Evolutionary-ELM neural networks were imported. Dot answers were plotted to linear regression.

The growth model forecasting results ELM calculated Activation Function found that Sigmoid Function predicted Brahman X Charolais crossbred beef cattle, from the forecast of the start of rearing from the 12th months to the 24th months, 496.31 kilograms can be predicted. The growth forecasting equation coefficient of determination  $R^2=0.7222$ ,  $Y=30.49x - 235.450$  Brahman X Thai native beef cattle  $R^2=0.7652$ ,  $Y=21.861x-98.381$ , fed up to 24 months produces a weight of 426.283 kilograms, which was still unable to establish a good predictive model and statistically acceptable. The Weighted-ELM algorithm optimized ELM in case of data imbalance between 2 breeds. Weighted-ELM Linear Kernel calculation  $C=28$ , Brahman X Charolais was predicted about 602.286 kilograms.  $R^2=0.8510$ ,  $Y=29.514x - 106.05$ , Brahman X Thai native  $R^2=0.8256$ ,  $Y=25.958x - 114.05$  was predicted 508.942 kilograms. Low coefficient of determination would be very problematic to predict the response variable with greater accuracy, and there was also a high weight distribution. Therefore, Evolutionary-ELM was used based on the theory of Differential evolution and MP generalized inverse were computed for fitness, and the improved vectors in each were mutated vectors, compared with the original vector to have

better fitness values. It resulted in scatter and new population with better fitness values. This also resulted in the good growth rate of weight. 35 generations were adapted, Brahman X Charolais  $Y=30.562x - 129.40$  during the 20th months would be 481.84 kilograms of body weight. When fed continuously until the 24th months, it could be predicted an average weight of 604.088 kilograms, which had the best value  $R^2=0.9327$ ,  $RMSE=0.130$ ,  $MSE=0.107$ . Brahman X Thai native  $Y=28.098x - 164.37$  could be predicted for 509.982 kilograms  $R^2=0.9706$ ,  $RMSE=0.117$ ,  $MSE=0.083$ . In consequence, Evolutionary-ELM learned from factors that affect weight to 35 generations, the growth data was close to the vector line in a perfect positive correlation.

Forecasting with Evolutionary-ELM used the data from 50 % breed of beef cattle (F1), which is initially collected in Muang District, Phetchabun Province that attempted to breed 50 % (F1) breed development data to evolve to F2 and F3 in the future. In addition, there has been an Artificial Neural Network (ANN) forecasting study with linear regression (Pilajun, et al., 2019) which presented growth predictions from the relationship between the breed and the growth of beef cattle at birth weight up to 24 months. The experiment was conducted in Ubon Ratchathani University. Prognostic results of Lowline Angus x Thai native 50 % (F1)  $R^2=0.9681$   $Y=0.0108X + 13.22$  compared to Lowline Angus blood 25 % and Thai native blood 100 %  $R^2=0.584$ ,  $Y=0.246X + 21.9$ . The growth of Lowline Angus x Thai native cattle was higher than that of Lowline Angus and Thai native 100 %. Moreover, Lowline Angus x Thai native had the highest chart slope. This is the result of combining the advantages of each species to have a good adaptation to the tropical environment, with greater productivity. In addition, forecasting by Artificial Neural Network was developed as a model for estimating carcass weight of Hanwoo cattle during the slaughterhouse delivery period. The developed model is a useful algorithm for automation machine, which measures only a few carcass variables in the sample image at a glance (Lee et al., 2020). Further study can be used to

estimate carcass weight of Brahman X Charolais and Brahman X Thai native beef cattle, and additional control of feeding factors (Senarath et al., 2009).

## Conclusion

Prediction of Brahman X Charolais and Brahman X Thai native beef cattle in Mueang Phetchabun District by algorithm of Evolutionary-ELM is a model that can be adapted for beef cattle farming in small and medium-sized farms to keep up with the demand for the modern market and the premium market. Corresponds to the study on the production capability of Thai beef cattle farms, a single estimation technique was used through a maximum likelihood estimation method. Effects of socio-economic factors and farm-specific production management, farm size, and differences in concentrates and roughages used have a profound effect on technically inefficient cattle production. ELM, Weighted-ELM, and Evolutionary-ELM. In the agriculture, it is also found forecasting revealed that the Artificial Neural Network (ANN) model has also been found to be applied in various environment-related tasks to explore the appropriate approach to erosion depth, with plotted linear points as well.

Consistent with the support between the Department of Livestock, Mueang Phetchabun District and Beef Cattle Raisers Club, Phetchabun Province in trying to create a group of 250-350 kilograms medium-sized beef cattle, and they were upgraded to large-sized 550-650 kilograms beef cattle, which is a good weight for slaughter. In addition, the Department of Livestock Development, Muang Phetchabun District came to support and coordinate farm management cooperation, and all aspects of beef cattle farming together with food development researchers, including providing advice on beef cattle breeds that helps make money to Phetchabun Beef Cattle Farmers Club. It is

also a business plan to have a process of planning, production, ordering high quality, concentrate feed, and minerals in order to produce beef cattle to meet the needs of consumers who are in a specific market and reduce raising time between 2 - 2 and a half years.

## Acknowledgment

Thanks to the National Research Council of Thailand for allocating budget for research and innovation integration, in Fiscal Year 2020, National Research Bureau.

Moreover, thanks to beef cattle farms, Huai Sakae Sub-district, Mueang Phetchabun District, Phetchabun Province; Beef Cattle Farm of Faculty of Agricultural Technology and Industrial Technology, Phetchabun Rajabhat University, Research Laboratory of Animal Science Department; and a computer lab of Computer Technology Department, Faculty of Agricultural Technology and Industrial Technology, Phetchabun Rajabhat University

## References

- Bartlett, P. L. (1996). The sample complexity of pattern classification with neural networks: the size of the weights is more important than the size of the network. *IEEE Transactions on Information Theory*, 44(2), 525-536.
- Boonprong, S., Choothesa, A., Sribhen, C., Parvizi, N., & Vajrabukka, C. (2008). Productivity of Thai Brahman and Simmental-Brahman crossbred (Kabinburi) cattle in central Thailand. *International Journal of Biometeorology*, 52(5), 409-415. doi: 10.1007/s00484-007-0135-2
- Boyce, C., & Neale, P. (2006). *Conducting in-depth interviews: A guide for designing and conducting in-depth interviews for evaluation input* (Vol. 2). Massachusetts: Pathfinder International.
- Bunmee, T., Chaiwang, N., Kaewkot, C., & Jaturasitha, S. (2018). Current situation

- and future prospects for beef production in Thailand—A review. *Asian-Australasian Journal of Animal Sciences*, 31(7), 968-975. doi: 10.5713/ajas.18.0201
- Ghosh, R., & Verma, B. (2003). A hierarchical method for finding optimal architecture and weights using evolutionary least square based learning. *International Journal of Neural Systems*, 13(1), 13-24. doi.org/10.1142/S0129065703001364
- Huang, G. B., & Babri, H. A. (1998). Upper bounds on the number of hidden neurons in feedforward networks with arbitrary bounded nonlinear activation functions. *IEEE Transactions on Neural Networks*, 9(1), 224-229. doi: 10.1109/72.655045
- Huang, G. B., Zhu, Q. Y., & Siew, C. K. (2006). Extreme learning machine: Theory and applications. *Neurocomputing*, 70(1-3), 489-501.
- Khunchaikarn, S., Mankeb, P., & Suwanmaneepong, S. (2022). Economic efficiency of beef cattle production in Thailand. *Journal of Management Information and Decision Sciences*, 25(2), 1-9.
- Krasachat, W. (2008). Livestock production systems and technical inefficiency of feedlot cattle farms in Thailand. *Chulalongkorn Journal of Economics*, 20(2), 141-154.
- Labani, M., Moradi, P., Ahmadizar, F., & Jalili, M. (2018). A novel multivariate filter method for feature selection in text classification problems. *Engineering Applications of Artificial Intelligence*, 70, 25-37. doi: 10.1016/j.engappai.2017.12.014
- Lee, D. H., Lee, S. H., Cho, B. K., Wakholi, C., Seo, Y. W., Cho, S. H., Kang, T. H., & Lee W. H. (2020). Estimation of carcass weight of Hanwoo (Korean native cattle) as a function of body measurements using statistical models and a neural network. *Asian-Australasian Journal of Animal Sciences*, 33(10), 1633-1641. doi: 10.5713/ajas.19.0748
- Na-Chiangmai, A. (2002) *Current situation and development trends of beef production in Thailand*. In Allen, J., & Na-Chiangmai, A. (Eds), *Development strategies for genetic evaluation for beef production in developing countries* (pp. 93 - 97). Canberra: Australian Centre for International Agricultural Research.
- Ogino, A., Sommart, K., Subepang, S., Mitsumori, M., Hayashi, K., Yamashita, T. & Tanaka, Y. (2016). Environmental impacts of extensive and intensive beef production systems in Thailand evaluated by life cycle assessment. *Journal of Cleaner Production*, 112(Part 1), 22-31.
- Osothongs, M., Khemsawat, J., Sarakul, M., Jattawa, D., Suwanasopee, T., & Koonawootrittriron, S. (2016). Current situation of beef industry in Thailand. *Proceedings of International Symposium: "Dairy cattle beef up beef industry in Asia: Improving productivity and environmental sustainability"* (pp. 5-8). Bangkok: Swisotel Le Concorde.
- Pilajun, R., Thummasaeng, K., Sawasdiphan, S., Suwanlee, S., Inthisaeng, W., & Wanapat, M. (2019). Growth performance of Lowline Angus x Thai native crossbred beef under tropical condition. *Tropical Animal Health and Production*, 51(8), 2253-2261. doi: 10.1007/s11250-019-01940-z
- Senarath, S., Thummasaeng, K., & Suriyapat, W. (2009). Protein requirement for maintenance of yearling Thai native cattle. *JIRCAS Working Report*, 64, 83-85.
- Steinfeld, H., Wassenaar, T., & Jutzi, S. (2006). Livestock production systems in developing countries: Status, drivers, trends. *International Office of Epizootics*, 25(2), 505-516.

- Storn, R., & Price, K. (1997). Differential evolution-A simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11(4), 341-359.
- Thapa, G. B., Lam-Estrada, P., & Lopez-Bonilla, J. (2018). On the Moore-Penrose generalized inverse matrix. *World Scientific News*, 95, 100-110.
- Zhu, Q. Y., Qin, A. K., Suganthan, P. N., & Huang, G. B. (2005). Evolutionary extreme learning machine. *Pattern Recognition*, 38(10), 1759-1763. doi: 10.1016/j.patcog.2005.03.028.
- Zong, W., Huang, G. B., & Chen, Y. (2013). Weighted extreme learning machine for imbalance learning. *Neurocomputing*, 101(1-3), 229-242. doi: 10.1016/j.neucom.2012.08.01